An Experiment on Case–Based Decision Making*

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Abstract

We experimentally investigate the disposition of decision makers to use case–based reasoning as suggested by Hume (1748) and formalized by Case–Based Decision Theory (Gilboa and Schmeidler, 1995). Our subjects face a monopoly decision problem about which they have very limited information. Information is presented in a manner which makes similarity judgements according to the feature matching model of Tversky (1977) plausible. We provide subjects a "history" of cases. In the 2×2 between–subject design, we vary whether information about the current market is given and whether immediate feedback about obtained profits is provided. The results provide support for the predictions of Case–Based Decision Theory, particularly when no immediate feedback is provided.

JEL Classifications: C91; D01; D81

Keywords: Case–Based Decision Making; Case–Based Reasoning; Heuristics; Limited Information Environments; Similarity

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1 Introduction

Considerable decision making in economics occurs in complex environments in which the decision maker's knowledge of the payoff function she faces is severely constrained. Very little is known about decision making procedures in such environments. Expected utility theory does not seem plausible in such situations and, furthermore, cannot be used to make meaningful predictions. It seems reasonable to suppose that people use a variety of procedures or decision making algorithms in such complex environments in which the decision maker's information is severely limited.

A theory of decision making which is suitable for complex environments follows from the ideas of the late Scottish philosopher David Hume (1711-1776). According to Hume (1748), "From causes which appear similar we expect similar effects." Hume went on to assert that "This is the sum of all our experimental conclusions." A recent formulation of decision making by Gilboa and Schmeidler (2001) provides a formalization of the ideas of Hume. In Gilboa and Schmeidler's Case–Based Decision Theory (CBDT) actions are evaluated according to the similarity weighted sum of payoffs they have yielded in similar problems.

In this paper we test whether decision makers use case–based reasoning in making their choices when given information that makes similarity judgements of a particular kind salient. Specifically, a feature–based similarity function (Tversky, 1977) seems plausible given the description of the decision problem the subjects face in our experiment. Given the salience of the feature–based similarity function, we are able to predict the choices that a case–based decision maker (DM) would make and can compare those predictions with actual behavior of participants in the experiment. This allows us to test whether our subjects employ CBDT, assuming feature–based similarity, in their decision making.

This paper is not aimed to test the (axiomatically developed) models of either Gilboa and Schmeidler or Tversky, in which case it would be more suitable to test if people behave according to their respective axioms. Nor, is this paper aimed at deriving the similarity functions people use. For this a very different experimental design would be optimal. Rather, we aim to see if the combined models have predictive power in environments in which expected utility theory has little predictive power. Specifically, we investigate if people choose according to CBDT in an environment (decision making task) where the assumption of feature–based similarity seems plausible.

While CBDT has been used in applied work in economics (e.g. financial markets, Guerdjikova, 2002 and 2003; housing markets, Gayer *et al.*, 2007; and capacity planning, Jahnke *et al.*, 2005), little experimental evidence has been gathered by economists to test the plausibility of the reasoning suggested by Hume which is distinct from what is usually assumed in economics. Ossadnik *et al.* (2013) find support for the predictive power of CBDT in repeated decision problems of structural ignorance. Our paper provides a first such test for a one–shot decision problem.

CBDT is not proposed as an alternative to or a generalization of the dominant expected utility theory.[1] It is thought to be suitable in environments which are sufficiently complex or in which the decision maker's information is severely limited so that the expected utility approach can not plausibly be used. In such situations, the decision maker may be more likely to rely upon her past experiences to evaluate current choices and reason in the manner suggested by Hume.

In order to test the predictions of a simple variant of CBDT and feature based similarity, we study production choices of a monopolist who is producing for several independent markets about each of which she has some

[1] For a formal relation between expected utility theory and CBDT see Matsui (2000).

knowledge of "past cases." In this environment, a case–based decision maker employing a feature–based similarity function would compare the market conditions of her "past cases," or "memory," to the market conditions she is currently facing and use that similarity measure to weigh the past outcomes of each of her production choices.

We employ a 2×2 design, in which we first contrast behavior in situations in which CBDT can be used with situations in which it cannot be used. We do this by comparing the choices of a monopolist who has some information about the current market conditions with choices when the monopolist does not have such information. In the latter the monopolist has no information with which to make a (feature-based) similarity comparison. Second, we analyze if immediate feedback about the obtained profits makes the subject more (or less) prone to use CBDT. The provision of such information may potentially confound the use of the simple versions of the models we test. We do this by either revealing profits from a market right after a production choice is made or delaying such feedback until production choices have been made for all of the markets.

Our results provide some support for CBDT. First of all, as expected, observed choices are different when participants are given information about the current market alongside a "market history" compared to when such information is not given. More importantly, we find that for almost all participants CBDT (coupled with feature based similarity) predicts more choices correctly than a random choice model. For a significant subset of participants CBDT predicts more than half of their choices correctly, and for a smaller, yet substantial subset, CBDT predicts more than two thirds of their choices correctly. The support for CBDT is stronger when payoff information is delayed until the end of the experiment. We interpret this as suggesting that CBDT (coupled with feature based similarity) is more salient when additional information about the performance of the DMs choices is not immediately provided because such information alters the decision making procedure (and/or the similarity relation) used by the DM.

While feature–based similarity seems to be very salient given our design, other similarity relations are plausible. For example, subjects could believe that the production choice with the highest payoff in memory will yield the highest payoff in the current market. We find that if payoff information is given immediately after production choices for each market are made, equally many participants seem to be guided by CBDT as by the simple heuristic that assumes that similar production choices yield similar profits independent of how similar the current market is to the scenario in memory. However, when such information is not given, CBDT predicts more choices correctly.

The remainder of the paper is organized as follows. Section 2 introduces CBDT and the notion of similarity. It gives a motivation for the specific functional form of similarity that we are using. Section 3 explains the experimental design. Section 4 states the predictions and our hypotheses. Section 5 discusses the experimental results and Section 6 provides concluding remarks. Appendix A contains a sample set of instructions and Appendix B provides additional individual data.

2 Preliminaries

2.1 Case–Based Decision Theory

Often times, decisions have to be made with very little information about the underlying environment. Consider the following example where only limited information is available:

> *The manager of a firm is looking to hire a technician for her newly established IT department. Her choice set is given by the applicants for the job. She knows that she is looking for*

a technician who is highly skilled at computer networking, fluent in visual basic, and can lead and motivate the rest of the IT team. She, however, does not know how each candidate would perform if hired. For example, a candidate may be highly skilled in all of the requisite areas, but it may turn out that he is going through a painful divorce and is continuously late for work and often depressed. Or a candidate may display great leadership and organizational skills but may turn out to be very poorly skilled at computer networking. The more she thinks about it the more she realizes that other problems may also occur and that she has no way of knowing what they might be or how they might affect the company. The manager is facing uncertainty, ambiguity, and a lack of information on several dimensions.

There are several difficulties with fitting this problem into the framework of expected utility. First, the states of the world do not naturally suggest themselves. Second, imagining all of the possible outcomes for each action is not a trivial task. This would amount to imagining every possible thing that could happen once an applicant is hired and imagining all of those things for every possible applicant. Lastly, even after an action has been taken, the outcome may not reveal the realized state of the world or whether the action chosen was optimal. For situations like this, when DMs cannot be guided by expected utility theory, CBDT has been suggested as an alternative.

The basic premise behind CBDT is that a DM uses her past experiences (or the experiences of others) to help evaluate current choices, rather than relying on beliefs about certain states of the world occurring. In the above example, if each job candidate provided references, then the manager could use the candidate's previous performance to help assess how each candidate would perform if she was hired. In order to help evaluate past outcomes, an agent possesses a similarity function that quantifies how similar the current situation is to a past situation. The agent is assumed to compare the current situation to all available past situations. The more similar the current situation is to a past situation the more heavily the agent will weigh the outcome of that past situation. The agent is then assumed to choose the action that maximizes the sum of the similarity weighted outcomes of all past situations.

Formally, a case–based DM is assumed to have a memory, M, consisting of a set of *cases*. A case consists of a problem or situation, q, the action chosen in that situation, a, and the utility, $u(r)$, gained from choosing action a in situation q and receiving the result (or outcome or consequence) r. Gilboa and Schmeidler (1995) provide axioms under which a cased–based DM behaves as if he possesses a similarity function, $s(p, q)$, which evaluates the similarity between the current situation and any past situation. When confronted with a problem, p, the case–based DM chooses the action a that maximizes

$$U(a) = U_{p,M}(a) = \sum_{(q,a,r)\in M} s(p,q)u(r), \tag{1}$$

where $s\left(p,q\right)$ measures the similarity between the current situation p and some past situation q. When considering any action a, the case–based DM only concerns herself with past situations in which that particular action was chosen. If in a past situation action a was not chosen, then the result and the subsequent utility obtained in that situation are ignored.[2]

In other words, a case–based DM adds up, over all cases in her memory, the similarity weighted utility that each action has received.[3] Whichever

[2]For a version of case–based decision theory that allows the agent to use such information, see Gilboa and Schmeidler (1997).

[3]CBDT usually does not make any distinction between an action that resulted in zero utility and one that simply was not chosen, since zero utility is typically taken as the default aspiration level.

action has the largest sum is the action that is predicted to be chosen in the current situation. Note that this means that any action that has never been chosen in the past will not be chosen in the current situation unless all actions chosen in the past resulted in negative utility.[4]

2.2 Similarity

Let's reconsider the example of the IT manager. Assume the manager received equally outstanding references for two candidates (Betty and Bob) and she must decide between them. Suppose Bob's reference was from a previous job in which he designed and maintained webpages. However, Betty's reference was from a previous job in which she was the head of a large corporation's IT department and was responsible for maintaining all networking. It seems obvious that the similarity between the past situation in which Betty was hired and the manager's current one is greater than the similarity between the past situation in which Bob was hired and the current one. Therefore Betty's outstanding recommendation will receive more weight than Bob's and the manager will choose to hire Betty.

While the above example seems intuitive, we have to consider a specific form for the similarity function in order to obtain actual choice predictions from CBDT. While the notion of similarity has not been widely studied in the economics literature, it has been the subject of much discourse in the psychology literature (see Goldstone and Son, 2005 for an overview).[5] Most of the models of similarity can be divided into two groups: geometric models and feature–matching models.

Geometric models assume that the objects that are being evaluated can be represented in some n–dimensional space. The (dis)similarity between

[4]In such a scenario a case–based DM is assumed to randomly choose an action from the set of available actions that have not yet been chosen.

[5]See Rubinstein (1988) and Sarin and Vahid (2004) for previous applications in economics.

two objects is then calculated as some measure of distance between the two objects. The most typical measures are the Euclidean distance and the City–Block distance. While these models have desirable mathematical properties, experimental studies have shown that they do not do well in representing how subjects actually perceive similarity (see Goldstone and Son, 2005 and Tversky, 1977 for overviews).[6]

In response to some of these findings, Tversky (1977) developed a model of similarity that assumes that objects can be described by a set of features and that similarity is defined over the features that two objects have in common and those that they do not have in common. This allows an agent much more flexibility in measuring the similarity between two objects, and also allows similarity to be measured among objects that do not naturally lend themselves to placement in some n–dimensional space. Specifically, Tversky's model says that similarity is calculated in the following manner. Let A be the set of features associated with object a and let B be the set of features associated with object b. The measure of how similar a is to b is given by $s(a, b) = \theta f(A \cap B) - \beta f(A - B) - \gamma f(B - A)$, where θ, β, and γ are positive constants and f is an interval scale that represents the salience or prominence of various features. Thus, the similarity between two objects, a and b, is a function of the set of features the two have in common, those that a has but b does not, and those that b has but a does not. This allows the measure of similarity between a and b to be positive or negative and it allows the similarity between a and b to differ from the similarity between b

[6] In particular, several of the properties of the geometric models are consistently violated by experimental subjects. First, it has been shown that the identity property does not hold, i.e. subjects do not always perceive an object as identical to itself (see Podgorny and Garner, 1979). Second, actual similarity evaluations are not always symmetric (see Holyoak and Gordon, 1983; and Ortony *et al.,* 1985). For instance, a subject reporting that domestic cats are very similar to tigers does not necessarily indicate that the same subject will report that tigers are very similar to domestic cats. Lastly, the triangle inequality often does not hold, nor does transitivity (Tversky and Gati, 1982). Finding objects A and B very similar and objects B and C very similar does not necessarily indicate that the subject will find objects A and C very similar.

and a.

In order to remain within the bounds of Case–Based Decision Theory, we use a simplified version of Tversky's feature based similarity function when calculating its predictions in our setup. The underlying axioms of CBDT imply that the similarity function a case–based DM uses can only take on values between 0 and 1. To achieve this we choose $\beta = \gamma = 0$ to prevent the similarity function from taking negative values. We assume that all features are given the same weight when calculating similarity, i.e. it is not more important to have feature 1 in common than it is to have, say, feature 2 in common. We let f count the number of features two objects have in common. CBDT assumes that if two objects are identical then the similarity between them is equal to 1 and that it is equal to 0 if they have no features in common. To ensure this we set the parameter θ equal to the reciprocal of the maximum number of features two objects could possibly have in common.[7] With the additional assumption of $u(r) = r$ the decision problem of a case–based DM can be formulated as choosing

$$\max_a U(a) = U_{p,M}(a) = \sum_{(q,a,r)\in M} \theta f\,(p \cap q)\,r. \tag{2}$$

3 Experimental Design

Since this is the first experimental investigation of case–based decision making for one shot decision problems, there are several aspects of the design that need detailed discussion. We will first give a general description of the individual decision making framework we use and then explain why we made particular design choices. Special attention is paid to the manner in

[7] If one only knows if attributes are equal or not, one can represent it as the "city block" distance in a model where the new attribute a_{ij} is an indicator of the old attribute b_i and takes the value v_i. This is standard encoding of qualitative variables as indicator ones in econometrics.

which we induce the decision maker's memory, how the similarity between the current and the "past" problems is generated and how the complexity of the task is created.

Subjects acted as monopolists making production choices for 30 different and independent markets. In each market, the production choice was limited to one of four values: 50, 100, 150, or 200. Subjects were informed that their profits depended on their production choice and some market conditions. Four different marketing reports (scenarios) with information on "past" market conditions and production choices with resulting profits were displayed for each market. This provided the memory of the DMs. In half of the treatments subjects were informed about the current market conditions, in the other half they are not. In half of the treatments, after making a production choice, subjects were informed about their profits from that market and then moved on to the next market. Otherwise the feedback about the profits made in each of the markets was delayed until the end of the experiment. Table I summarizes our 2×2 between–subject design.

TABLE I:
THE 2×2 EXPERIMENTAL DESIGN

		Information	
		Past + Current	Past Only
Feedback	Immediate	39 subjects	30 subjects
	Delayed	33 subjects	31 subjects

Figure 1 shows a screenshot of the experimental interface for the treatment in which immediate feedback and information about the current market conditions is given.[8] In the language of CBDT, the current problem is given by a *Current Market Report* that includes features of *Market Conditions* on

[8] Screenshots of the other three treatments are given in Appendix C.

the right hand side of the page. The cases in the DMs memory are given by four *Scenarios* that include features of the market conditions. Each case is listed with an act (*Production Value*) and an outcome/consequence (*Profit*).

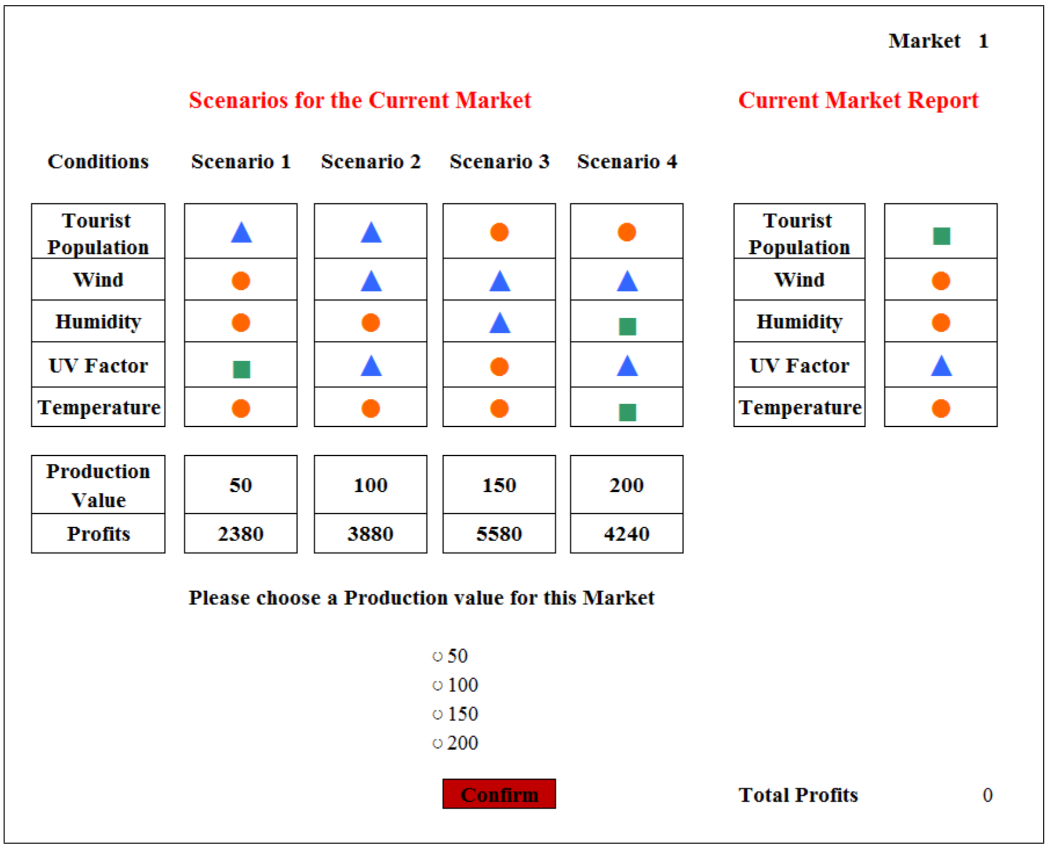


Figure 1: Screenshot

One–shot decisions, independence of markets: In the instructions, and in the questionnaire following the instructions, we made sure that the subjects understood that the markets were independent from one another and that decisions made for one market would not affect any other market.[9]

[9] We chose to work in a framework where a DM never encounters the same problem twice. CBDT can, however, be modified to study choices in repeated decision problems (see, e.g., Gilboa and Schmeidler, 2001).

To emphasize that the markets were independent, a different set of market conditions was displayed in each market.

Memory: Control over the memory is important in order to make accurate predictions in CBDT. Firstly, we wanted to minimize the effect of any "home–made prior," i.e. memory the subjects brought to the lab with them. We did this by the novel manner in which we presented the decision problem and, in particular, our use of symbols. We believe the use of symbols rather than numbers made it more difficult for subjects to use their extant memory to deal with the problem at hand. Our use of symbols will be discussed in more detail when we talk about how we induce similarity.

Secondly, we did not want subjects to "build" a memory over the 30 different markets they faced during the experiment. We, therefore, emphasized that markets were independent. We induced a separate and different "memory" for each of the 30 markets. We did this by displaying four scenarios in each market. The displayed scenarios and the market conditions which they represented were different for each market. For each of the four scenarios, a different production choice and the profit that would have been earned given that production choice and the market conditions, was displayed.[10] To ensure that in each market each production value was a possible choice for a case–based decision maker, each memory contained one observation of each possible production value. Thus, the memory of each subject, for each market, consists of 4 scenarios and their descriptions (i.e. the market conditions and their corresponding symbols, the production choices, and resulting profits).

A case–based decision maker would calculate the similarity between the current market and the four cases (i.e. four scenarios) in her memory and use the similarity measure to weigh the profit that was "received" in each

[10]See Appendix A for a full set of the instructions.

case. The production value with the highest similarity–weighted profit is the one that a case–based decision maker would choose. The displayed market conditions and production values were randomly generated for each market. While it was possible for profits to be negative for a given decision, overall accumulated profits could never be negative.

If our subjects adjusted their behavior in response to the actions they chose (in unrelated markets) and the profits they obtained, then the four cases that we provided would not be the only basis for their decisions. That is, if the subjects were (erroneously, because the markets were unrelated) learning through reinforcement, then our assumptions would not be met and we would have lost control. We therefore vary whether subjects are informed about their profits from each market immediately after they make a production choice or not. If the (profit) feedback is delayed, all profits from all markets are displayed at the end of the experiment. The delayed feedback condition eliminates most kinds of reinforcement learning that could have potentially occurred across the independent markets.

Similarity: In an attempt to make the use of a feature–based similarity function salient we displayed all values of the market conditions as symbols. Subjects were told that the marketing report in each market was transmitted by their marketing department with an error that resulted in all numbers/levels being erased and only symbols being reported.[11] Subjects were informed that the error was consistent, i.e. the same symbol always meant the same thing for the same market condition, while it could mean different things for different market conditions. All participants faced the

[11] We used a square, a triangle and a circle. To distinguish shapes easier, we colored them. Squares were always green, triangles blue and circles orange. Since the experimental interface included geometric forms and colors, we asked participants after the experiment how they interpreted those. In particular, participants were asked: "If it were the case that the three symbols you saw during the experiment [symbols again given here] stood for high, medium and low, which symbol would you think stood for which level?" We found no correlation between any symbol and level.

same markets in the same order with the same set of scenarios given to them.

There are several reasons we chose to use symbols instead of actual values. Firstly, it eliminates geometric similarity considerations. Secondly, it reduces home–made priors. What we discovered in pilot experiments was that people treated large values of some features closer to other large values of the feature (and, hence, more similar than) smaller values of the feature. This is problematic for the simple (original) version of CBDT where similarity can either be 0 or 1. Furthermore, the values interacted with the features of the decision problem in a way that brought into the lab things we wanted to control for. For example: home–made priors of the following type were possible: "The temperature is very high today so I shouldn't produce very much because it's too hot for buyers to want to be out shopping." These observations suggested that the subjects were using similarity relations in their memory *before entering the laboratory* to inform the decision task in the laboratory. We wanted control over the subject's memory and did not want them to be able to (systematically) use their earlier memory for the decision tasks they faced in the lab. We believe the use of symbols makes it more difficult for people to bring their "real world" memories into the lab in any systematic way. It therefore allows us to test the theory better and with less interference from similarity relations the subjects may have developed from life outside the lab. We acknowledge that this might restrict the external validity of our experiment but we wanted to test the theory as cleanly as possible. We also acknowledge that the use of symbols could lead the subjects to think in terms of similarity. However, we believe that even with values (rather than symbols) people use similarity judgements. With symbols, we believe, they are more likely to use feature–based similarity as we assume. That is, we feel the use of symbols gave us better control.

Complexity: CBDT was conceived under the premise that in many decision problems states of the world are neither naturally given nor can they be simply formulated. Furthermore, it assumes that often even a comprehensive list of all possible outcomes is neither readily available nor easily imagined. In order to generate a complex enough environment, in which it is impossible for subjects to figure out potential states of the world or associated outcomes, we let the profit of the monopolist in a given market depend on many different variables that we call market conditions.

We used a total of 12 different market conditions. Subjects, however, did not know this. In each market, subjects were only given information on a random subset of 5 conditions.[12] Deriving predictions using a linear feature–based similarity relation assumes that all market conditions are equally weighted. We therefore did not want to give the names too much economic meaning and have subjects trying to guess which ones might influence their sales and therefore their profits as such a behavior would have violated the assumption of equal weights, we decided to name our market conditions as neutrally as possible. We came up with Tourist Population, Wind, UV Factor, Chance of Rain, % of Population Female, Humidity, Traffic Conditions, Temperature, Literacy Rate, Median Age, # of Potential Buyers, and Gas Price. Subjects never saw the last two conditions: # of potential buyers or gas price. Subjects did not even know that these conditions existed. For each market each condition was randomly chosen to have a value of either 1, 2, or 3.

We generated 15 different payoff functions and used each one twice. The payoff functions were not additively separable, varied according to which choice maximized the payoff and differed in the "penalty" for making a non–optimal choice.[13] Of the 12 market conditions a randomly selected set of 4 would enter the payoff function in each market. Out of the 5 conditions

[12] The market conditions displayed in the hypothetical scenarios are the same as those given in the marketing report so that similarity comparisons could be made between them.

[13] To ensure comparability across treatments, the subjects faced the same payoffs function in the same order.

that the subjects saw in each market, 3 were payoff relevant and the other 2 were not. As mentioned before, two conditions (# of potential buyers and the gas price) were never reported to the subjects. One of these was chosen at random to enter the payoff function in each market.[14]

We furthermore vary whether subjects are given information about the current market in addition to the four scenarios in the induced memory. The treatment without current information acts as a control treatment. Subjects cannot use case–based reasoning to make their choices if there is no information about the current decision problem. Note that all subjects in all treatments saw the same sequence of market conditions and the underlying profit functions were the same. Hence, we can make direct comparisons between the different treatments. Observed choices in the treatment without current which coincide with choices that are in agreement with the predictions of CBDT in the treatment with current information are due to factors which do not involve case–based reasoning. Only the additional choices (in the treatment with current information) in line with CBDT can be attributed to case–based reasoning. Note that instead of a treatment that does not provide the current market report, we could have displayed the current market report using incomparable information. We prefer the cleaner comparison between a treatment with current market conditions and one without current market conditions as anything else might have confused subjects and introduced other errors into the decision making process.

The experiments were conducted at the Economic Research Laboratory at Texas A&M University. Invitations to participate in the experiments were randomly sent out to undergraduate students in our database of about 1,200 from a diverse background of majors. The experimental interface was programmed in zTree (Fischbacher, 2007). On average the experimental

[14] An example of a payoff function is $\pi(.) = 50q - 0.009(3C_1C_2 - C_3C_4)q^2 - 1150\ln(q-48)$, where q is the quantity chosen and C_i indicates market condition i.

sessions lasted about 90 minutes and average earnings were \$16.32 with a minimum of \$10.37 and a maximum of \$19.56. Additionally, a \$5 showup fee was paid).[15] We tested the participants' comprehension in a questionnaire after reading the instructions. We individually checked their answers and corrected them in private if necessary. We went over all questions again aloud.

4 Predictions and Hypotheses

Using the screenshot from Figure 1 as an example, we would like to demonstrate how Case–Based Decision Theory with a feature–based similarity would make its predictions.[16] For each scenario, a case–based DM would count the number of conditions for which the symbol that is given in the scenario matches the symbol that is given in the current market report. Looking at Figure 1, we can see that scenario 1 has three conditions in which the symbols are the same as in the current report (namely wind, humidity and temperature). Scenario 2 also has three conditions that show the same symbols (namely humidity, UV factor and temperature). Scenario 3 and 4 each have one match (temperature and uv factor, respectively). A case–based DM then weighs the received profits in each scenario with the similarity count divided by 5, the total number of conditions and hence possible matches. Hence, 2380 gets a weight of 3/5, 3880 gets a weight of 3/5 and 5580 and 4240 each get a weight of 1/5. The similarity weighted profit from scenario 2 is the biggest and therefore a case–based DM should choose 100 in this market.

As for hypotheses, we first would like to establish that the provision of information about the current market conditions makes a difference in the

[15] Sessions varied in size from 4 to 18 participants.

[16] The relatively coarse and simplified version of the feature based similarity function that we employ makes the same predictions as a more generalized similarity function used by Gilboa *et. al* (2006) in all but one market.

choice behavior. We then postulate that this difference in choices is driven by similarity comparisons that subjects make and incorporate into their decision making through case–based reasoning.

H1: Choices in the treatments when current information is provided are different from choices in the treatments when such information is not provided.

H2: Choices in the treatments when current information is provided are in line with case–based reasoning. Hence CBDT with feature–based similarity is a good predictor of choices.

We do not have any hypothesis regarding the timing of the feedback. Intuitively, immediate feedback could interfere with our control over the subject's memory and make predictions of CBDT less precise as it could lead to subjects "learning" across markets. Past choices that seemed "satisfactory" could be reinforced and hence alter the basis of similarity comparisons.[17] We, therefore, check that no such learning was occurring in our analyses of the data.

5 Experimental Results

5.1 The Effect of Current Information

For each market, we conduct Chi–square tests to determine whether behavior differs when current information is given compared to when it is not.[18] In 14/30 (13/30) markets, choices in the treatment with current information

[17] Note that subjects did not even know the range of payoffs. Any judgement regarding the satisfaction through the evaluation of obtained payoffs is highly subjective.

[18] For the non–parametric tests used in this paper see Siegel and Castellan (1998).

are significantly different from choices in the treatment without current information when immediate (delayed) feedback is provided. These Chi–square tests have to be interpreted with care, however, as frequencies are rather low in some cells. The test tends to falsely not reject the null, i.e. choices show up as not significantly different from one another when they actually are (Type II error). We tend to interpret this conservative reading as support for our first hypothesis: *Choices in the treatments when current information is provided are different from choices in the treatments when such information is not provided.* The question remains as to how people make use of the provision of current information. Do they do so in the form of case–based reasoning?

5.2 Absolute Performance of CBDT

We first analyze how well the predictions of CBDT match observed behavior.[19] We are interested in predicting individual behavior rather than the average behavior of participants. We therefore calculate the mean squared deviations (MSDs) of the theoretical prediction from the observed choice for all 30 decisions a subject faced. We do this for each subject (individual data can be found in Appendix B, Table V). If every market's choice coincides with its CBDT prediction a subject would show a MSD of 0, and if the subject never selected as predicted her MSD would equal 2. If a subject was choosing randomly, one could interpret this as meaning that her choices coincide with theoretical predictions 25% of the time (since there are four choices to choose from). Given that CBDT is a deterministic model, it seems unsuitable to compare it to a probabilistic one where each entry in the prediction vector is 0.25.[20] We therefore establish the benchmark of random

[19] For a first analysis we assume that the aspiration level of a case–based decision maker is zero. This aspiration level can be easily adapted as we discuss in section 6.2.

[20] Such a calculation would lead to a MSD of 0.75. In general, the calculation of MSDs favors probabilistic models over point predictions (see Selten, 1998 for an axiomatization of quadratic scoring rules).

choice as being correct 25% of the time and obtaining a MSD of 0 and being incorrect 75% of the time realizing a MSD of 2. The average over all 30 decisions is then 1.5. Table II shows that CBDT predicts behavior better than a random choice model for 97% (79.5%) of subjects in the treatment with delayed (immediate) feedback. In order to see how many choices are predicted correctly by CBDT we establish two other benchmarks: (1) predicted choices coincide with observed choices at least half of the time (in 15 out of 30 markets), and (2) predictions coincide with observed behavior at least two–thirds of the time (in 20 out of 30 markets). Table II summarizes the results and provides support for hypothesis 2 that subjects make use of current information in the form of case–based reasoning.

Table II:
Observed Frequencies of individual MSDs
when comparing choices to CBDT predictions

	CBDT predicts correctly more often than:		
	Random (>7 choices) (MSD<1.5)	Half (>15 choices) (MSD<1)	Two–Thirds (>20 choices) (MSD<0.67)
Immediate Feedback	79.5% (31/39)	25.6% (10/39)	15.4% (6/39)
Delayed Feedback	97.0% (32/33)	39.4% (13/33)	18.2% (6/33)

5.3 An Alternative Heuristic and Relative Performance of CBDT

Since EUT is not a reasonable alternative decision making procedure in the environment we consider, we look for simple decision making principles that deliver predictions in our environment and that can pose as alternatives to CBDT (other than the random choice model). Heuristics, or rules of thumb, referring to useful and indispensable cognitive processes for solving problems that cannot be handled by logic and probability theory (e.g., Polya, 1954), suggest themselves. Heuristics allow people to make decisions by simplifying the complex environments people often face (e.g., Simon, 1955).

Gigerenzer and Goldstein (1996) introduced such a fast and frugal algorithm, called "Take the Best" for a search problem. While we use the same basic principle as "Take the Best," the implementation of this heuristic is quite different (and much simpler) in our environment. As such we call this heuristic the "Max–Heuristic" in our setting. Our subjects are given four scenarios for each of the decisions that they are facing, with each possible production value being chosen and displayed once. The Max–Heuristic (or, MAX) would predict that a DM chooses the production value that returned the highest profit among those four scenarios. For example, looking at the screenshot in Figure 1, a DM is predicted to choose 150, as it returned the highest profit, 5580, of all the displayed production values. Note that in the treatment where information about the current market is given this would mean that DMs ignore that information. In the treatments when such information is not given, MAX seems a rather suitable. Note also that even MAX is based on similarity arguments. The similarity notion is, however, very different. MAX is entirely based on the assumption that similar production choices yield similar profits independent of how similar the current market conditions are to the scenarios in memory.[21,22]

[21] Choices predicted by CBDT are different from those predicted by MAX in all but 7 markets. Note that if only the rank of profit were available instead of the exact profit, then the results should not change according to the MAX heuristic. Since the focus of this paper is not the MAX heuristic, we do not vary the design to investigate its robustness.

[22] As suggested by Karl Schlag, an alternative rule of thumb could be to prioritize similarity, i.e., choose the production value whose scenario has the most features in common with the current report (as long as its profit is positive). If there are more than one of those production values, choose the one with the highest profit from this set. If the production value whose scenario has the highest number of features in common with the current report has a negative profit associated with it, choose the one that has the next highest number of features in common. Again, if there are more of those, choose the one that has the highest profit associated with it. In our experimental setup predicted choices

Table III demonstrates that CBDT is a better predictor than MAX when feedback is delayed and current information is provided (i.e., individual MSDs of observed choices from predicted choices are lower for CBDT). When feedback is immediately provided and current information is given, CBDT does not predict a larger proportion of choices when compared to MAX, indicating that equally many participants seem to be guided by CBDT as are guided by MAX.

TABLE III:
CBDT VS. MAX IN TREATMENTS W/ CURRENT

Robust Rank Order Test	**z–statistic**
Immediate Feedback	0.03
Delayed Feedback	-4.27^{**}

Note: ** indicates significance on the 5% level

Table IV summarizes the performance of MAX compared to the three previously established benchmarks. Comparing the performance of CBDT (as summarized in Table II) when information about the current market is given and feedback is delayed with the performance of MAX (as summarized in Table IV) we find that CBDT predicts better than random for more subjects than MAX (Test of Equality of Proportions: z–value= 3.61, one–tailed $p < 0.001$).[23] In this treatment, CBDT predicts more than half and more than two thirds of the choices correctly more often than MAX (Test of Equality of Proportions: z–value= 2.87 (1.51), one–tailed $p = 0.00211$

of such a heuristic coincide with predicted choices of CBDT in all but three markets. We therefore do not separately analyze its predictive power.

[23]The specific test statistic is $z = (p_1 - p_2)/S_{p_c}$, where p_i is the proportion in subsample i, and $S_{p_c} = \sqrt{p_c(1-p_c)(\frac{1}{N_1} + \frac{1}{N_2})}$ is an estimate of the standard error of the difference in proportions, $p_1 - p_2$. p_c is an estimate of the population proportion under the null hypothesis of equal proportions, $p_c = (p_1 N_1 + p_2 N_2)/(N_1 + N_2)$, where N_i is the total number of subjects in subsample i (see Glasnapp and Poggio, 1985).

(0.0655)). When feedback is immediately provided, CBDT and MAX are equally good when compared to a random choice model or when comparing the number of choices predicted correctly (more than half and more than two thirds, respectively).

Table IV:
Observed Frequencies of individual MSDs
when comparing choices to MAX predictions

		Random	Half	Two–Thirds
Max–Heuristic predicts correctly more often than:				
		(>7 choices)	(>15 choices)	(>20 choices)
		(MSD<1.5)	(MSD<1)	(MSD<0.67)
Immediate	w/ Current	87.2% (34/39)	20.5% (8/39)	10.3% (4/39)
Feedback	w/o Current	93.3% (28/30)	33.3% (10/30)	26.7% (8/30)
Delayed	w/ Current	60.6% (20/33)	9.1% (3/33)	6.1% (2/33)
Feedback	w/o Current	80.6% (25/31)	29.0% (9/31)	12.9% (4/31)

Figures 2 and 3 graphically show the performance of CBDT predictions. Performance is evaluated by how many of the 30 decisions are predicted correctly, i.e. coincide with actually observed choices. The cumulative density of observed choices coinciding with predicted choices is plotted for the different treatments.[24] To make comparisons easier, two vertical lines, referring to 1/4 (random) and 2/3 (two–thirds) of the decisions, are included. The further the lines are to the right, the more often do the predictions of CBDT coincide with observed choices. The lower the lines the higher the proportion of subjects for whom predicted choices coincide with observed choices. The figures can be tied back to Tables II and IV. In addition to the benchmark of 7.5 correct choices for a random model, we simulated 100 subjects to make 30 decisions randomly. We plot the cumulative probability distribution of the simulated choices that coincide with actual choices and add them to Figure 2 for comparison.

Figure 2 clearly shows that CBDT does better than a random model. If one takes 7.5 as the average of correctly predicted choices by the random

[24]Each subject is characterized by one number that corresponds to how many of her observed choices coincide with theoretically predicted choices.

model, than Figure 2 shows that for 79.5% of the subjects CBDT does better (as indicated in Table II) when feedback is immediate.[25] This percentage is 97% when correctly predicted choices of CBDT are compared with randomly correctly predicted choices when feedback is delayed. However, testing the distribution of correctly predicted choices reveals no difference between delayed and immediate feedback (Kolmogorov–Smirnov test, $p = 0.177$).

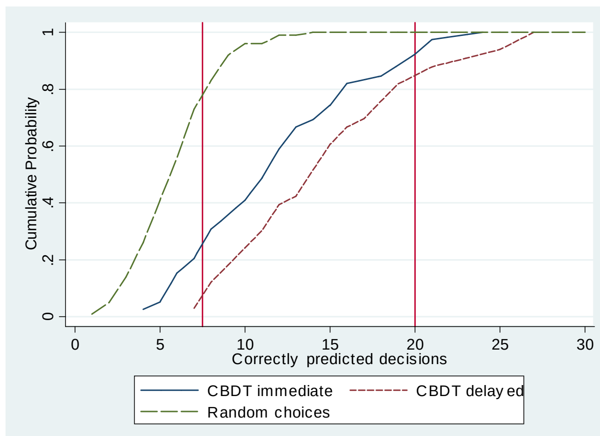
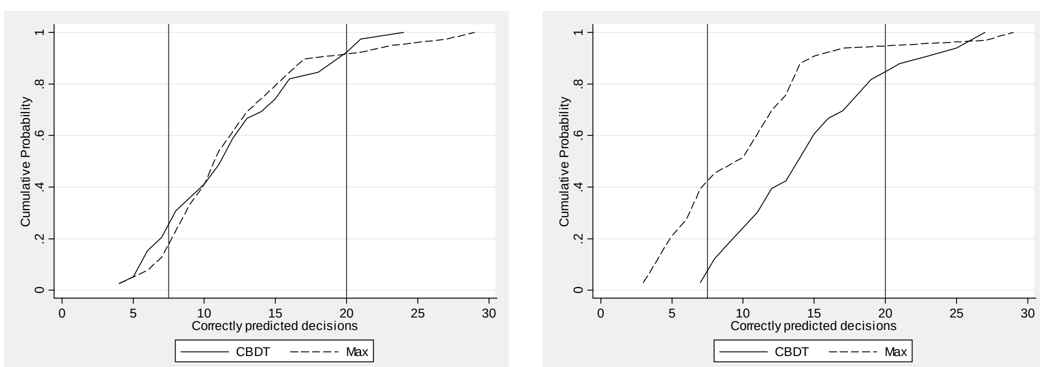


Figure 2: Cumulative density of choices in line with CBDT predictions



(a) Immediate Feedback

(b) Delayed Feedback

Figure 3: Cumulative density of choices in line with predictions of CBDT or MAX

[25] These percentages are 100% minus the percentage that is found at the intersection of the solid line with the vertical line at 1/4.

Figure 3 compares the performance of CBDT with the performance of MAX. Panel (a) shows that when feedback about profits is immediately given performance does not differ (Kolmogorov–Smirnov test, $p = 1.000$). Panel (b) illustrates that CBDT outperforms MAX when feedback is delayed (Kolmogorov–Smirnov test, $p = 0.014$).

6 Further Analyses of the Results

6.1 Learning

There are different types of learning that could take place in our experiment. First, it seems natural to ask whether our subjects learn to become case–based decision makers. If this was the case, we should observe that individual MSDs (calculated with respect to the CBDT predictions) get smaller over time. Second, our subjects could learn across markets. For the purpose of our paper it is important that there be no such learning. In the immediate feedback treatment, in which subjects received feedback about their performance after each decision, it could be conjectured that some kind of reinforcement learning could be taking place.

In order to address the first type of learning we calculate the average of an individual's MSDs over the first 15 markets and compare this with the average of the same individual's MSDs (when calculated with respect to the CBDT predictions) over the second 15 markets (see Appendix B for the individual data). We find that 44% (17/39) show a smaller MSD in the second half of the experiment when current information is provided and immediate feedback is given. This percentage is not significantly different from the percentage of those that show an increase in their MSDs, 38.5% (15/39), (Test of Equality of Proportions, z–value= 0.46, n.s.). The same holds when feedback is delayed and information about the current market is given (18/33 (MSD decreases) vs. 14/33 (MSD increases), Test of Equality of

Proportions, z–value= 0.92, n.s.). We can therefore conclude that subjects do not tend to use CBDT more often over time, i.e. there is no learning towards becoming a case–based DM. Interestingly, participants seem to follow MAX more often over time when immediate feedback is given and no information about the current market is given (21/30 (MSD decreases) vs. 8/30 (MSD increases), Test of Equality of Proportions, z–value= 3.36, one–tailed $p < 0.001$). Immediate feedback is driving this result. The MSDs with respect to MAX do not go down when feedback is delayed (14/31 (MSD decreases) vs. 10/31 (MSD increases), Test of Equality of Proportions, z–value= 1.04, n.s.).

In order to address the second type of learning, we derive predictions from a reinforcement learning type model in which agents only have information about the action they take and the payoff it obtains. We use the payoff assessment learning model (Sarin and Vahid, 1999) in which a DM is assumed to evaluate actions (j, k) according to their (payoff) assessments or attractions (q_j, q_k).[26] The DM chooses the action with the highest attraction. If she chooses action k at time t and receives a payoff of x, then the attraction of action k at time $t+1$ becomes $q_k(t+1) = (1-\lambda)q_k(t)+\lambda x$, where $\lambda \in [0, 1]$, while for all other possible actions $j \neq k$, $q_j(t+1) = q_j(t)$. We assume initial assessments equal to the average of the payoffs seen in the first four scenarios of market 1 and find the λ that best fits the data (through a grid search method with 0.1 increments). We use this to calculate the individual MSDs for each subject. We find that the payoff assessment model does better in the treatments with immediate feedback compared to when feedback is delayed (in which case, it is equivalent to the random choice model). However, it only predicts choices more than half of the time for one subject out of all the treatments. Its general performance is close to random (MSD = 1.5).[27]

[26] Given that our paper aims at explaining individual behavior, we do not simulate a probabilistic reinforcement learning model (e.g., Roth and Erev, 1995) which would either lead to comparing choices with a probability vector or analyzing population means.

[27] Given that there is not much variance in individual MSDs, we determine overall per-

We therefore feel confident that there is not much learning going on across markets.

6.2 CBDT with Different Aspiration Levels

As mentioned earlier, we derive CBDT predictions assuming an aspiration level of zero. This can be easily adjusted to include other aspiration levels. We redid our analysis and set the aspiration level equal to the average payoff of all four cases in a DM's memory. We do not observe any participant in the treatments when current information is provided for whom the adjusted CBDT predicts more than two–thirds of their choices correctly. Unfortunately, the new predictions of CBDT with average aspirations often coincide with the predictions of the MAX. This makes any distinction between these two alternative decision making processes impossible. A different design is needed to distinguish between alternative aspiration levels for CBDT.

7 Conclusion

We design an experiment to test whether subjects use case–based reasoning combined with feature based similarity in an individual decision making environment. Our design makes the use of a feature–based similarity relation salient. We find that when similarity comparisons can be made along the lines we hypothesize, decision makers seem to do so. In particular, for a significant subset of the participants CBDT predicts more than half of their choices correctly, and for a smaller, yet substantial subset, CBDT predicts more than two thirds of their choices correctly. Note that we are only assum-

formance by calculating the average MSD for each treatment. Interestingly, when no current information is given, the model that fits "best" gives a weight of 0.1 to the obtained payoff independent of whether immediate feedback is given or not. Behavior seems quite "backward" looking. When current information is given, 0.2 returns the lowest average MSD when immediate feedback is given. However, when feedback is delayed the lowest average MSD is obtained with a weight of 0.9.

ing a similarity function in order to derive predictions from CBDT. We are not actually testing for the plausibility or suitability of the similarity function. While we cannot distinguish between closely related similarity functions that our participants might be using, the strength of this paper lies in the fact that a rather coarse similarity relation can be used to make predictions that are borne out in the data, i.e. our design is robust to “small” changes in the similarity function.

It can be argued that our experimental design leads subjects to use the MAX heuristic. While that may indeed be the case, it only makes it more striking that some subjects do in fact behave as if they were case–based decision makers and choose to act as such despite the availability of the seemingly simpler MAX heuristic.

Our data reveal that CBDT seems more appropriate in situations where feedback is slow. This is reassuring as CBDT was conceived to be applicable in complex situations when other learning is not really possible. We think there are at least two reasons for this. First, when no immediate feedback is given, the proportion of people who use other, arguably simpler heuristics (like the Max heuristic) does not increase over time (unlike when immediate feedback is given). Second, as the payoff assessment simulation in section 6.1 shows, a very simple adaptive learning model describes behaviour better when immediate feedback is given as compared to when such feedback is not given, indicating that a model allowing for learning across markets tracks individual behaviour better than one that doesn’t. But, as the comparison with CBDT shows, an adaptive learning model that does not capture the notion of similarity is not as powerful in predicting individual choices as a model that incorporates similarity in a way that CBDT does.

It seems reasonable to suppose that people use a variety of procedures or decision making algorithms in complex environments in which the decision maker’s information is severely limited. Our results suggest that people seem to employ Hume–like reasoning. However, our findings also suggest that people may be using yet simpler decision making procedures, or heuristics, in these complex choice environments. As considerable decision making in economics occurs in such complex, informationally constrained, environments, it appears desirable to study further, both theoretically and experimentally, the decision making procedures agents use in such environments.

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Appendix A – Instructions

This is an experiment in the economics of decision making. Texas A&M University has provided funds for this research. If you follow the instructions and make good decisions, you can earn an appreciable amount of money. At the end of today's session, you will be paid your earnings in private and in cash.

It is important that you remain silent and do not look at other people's work. If you have any questions, or need assistance of any kind, please raise your hand and an experimenter will come to you. If you talk, laugh, exclaim out loud, etc. you will be asked to leave and you will not be paid. We expect and appreciate your cooperation.

During this session you will be acting as a firm who is selling a good. You will be selling your good to 30 independent markets. You can think of these as 30 geographically separated islands. In each of the 30 markets (islands) you are the only seller of the good. This means that nothing any other seller or firm does can affect you or your market. Each period represents a new market and you will have to make a decision about how many units you want to produce for that market. It is costly to produce this good and if you produce units that do not get sold in that market, you will NOT be able to keep those units for use in other markets. At the end of each period you will earn profits on the units of your good that you do sell in that market.

At the beginning of each period you will receive a Marketing Report that contains information regarding some Market Conditions for the current market. You can think of this as information about the market that has been gathered for you by the Marketing Department of your firm. Gathering this data is costly to your firm, as such your Marketing Department is not able to gather all information in every market. Therefore, the information that your Marketing Department does collect can vary from market to market. However, nothing you or anyone else does can change what information is gathered in any market.

After gathering the data the Marketing Department sends it to you. Unfortunately there is an error that occurs during that transmission. Instead of receiving the actual data all you receive is a list of the Market Conditions that were collected and a table of symbols representing the actual data.

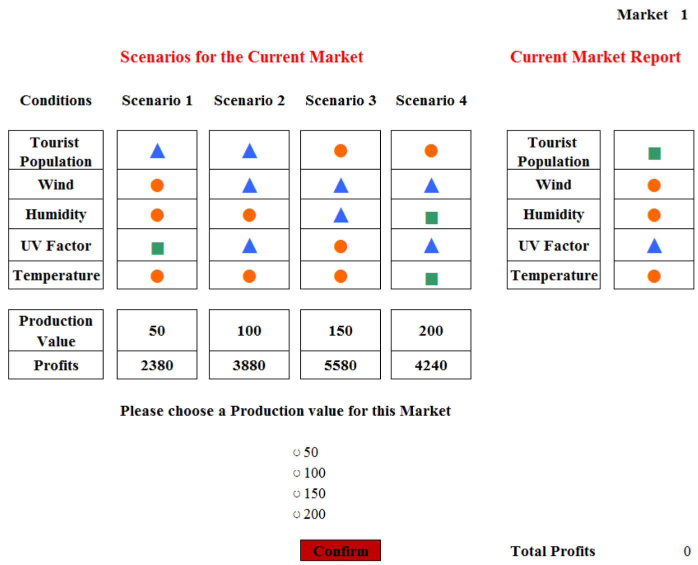
Fortunately the error is consistent. This means that identical symbols for a given Market Condition represent the same actual data. For instance, if the Marketing Department gathers data that says median income is $35,000 and a blue triangle gets transmitted, then whenever the Marketing Department reports $35,000 for median income it will be transmitted as a blue triangle in the Marketing Report. However, a blue triangle can also appear for other Market Conditions, where it does not necessarily stand for $35,000. For example, if the Marketing Department gathers data on a high inflation rate and this information gets transmitted as a blue triangle, then all Marketing Reports with a high inflation rate will have a blue triangle in the table for inflation rate.

After you have received the Current Marketing Report you will be asked to choose a Production Value of 50, 100, 150, or 200 units. Your Profits each period depend on your Production Value and may also depend upon some of the Market Conditions. After you have made your production choice, you will be informed of your Profits for that market. You will then proceed to the next market where you will be given the new market's Current Marketing Report. You will then be asked to choose a Production Value for that market. The session will continue in this manner until you have made production choices for 30 markets.

In order to help you with your decisions, for each market the experimenter has included four different scenarios. In each of these scenarios the experimenter was given a Marketing Report similar to the Marketing Reports that you will be given. The experimenter then chose a Production Value in such a manner that each of the four production choices was chosen once. The Profits reported in these scenarios are the profits that would have been earned in that market given the reported Market Conditions and the chosen Production Value. The Profits reported in these scenarios will NOT be included in your Total Profits. Your Total Profits consist only of those profits that you earn during the session, i.e. when you are making the production decision. Your Total Profits will be calculated by simply adding up the profits you earn in each of your markets.

Figure 1 gives an example of the decision screen. At the top right of the screen you will see labeled the current market. At the bottom right of the screen you will see your Total Profits, which will include all Profits you have earned so far. On the left side of the screen you will also see a table with the four scenarios for the current market. In the first column from the left you will see labels for the Market Conditions, the Production Values, and Profits. So in this market, your Marketing Department has gathered information on: the Tourist Population, the Wind, the Humidity, the UV Factor, and the Temperature. Looking at the symbols in the table you can see that there is a blue triangle for Tourist Population in Scenario 1 and Scenario 2. This means that the Tourist Population was the same in both of these scenarios. You can also see that there is a blue triangle for Humidity in Scenario 3. While this is the same symbol that was present in Scenarios 1 and 2 for the Tourist Population, it does not necessarily represent the same thing that it did for Tourist Population. Below the scenarios you will see the Production Values and Profits for those scenarios. Again, the Production Values were chosen so that each value was chosen exactly once. The Profits that you see are the Profits that would have been earned had the given Production Value been chosen with the given scenario. On the right side of the screen you will see the Marketing Report for the current market, in the left hand column are the symbols representing the data from the report and in the right hand column are the labels for the different Market Conditions that are reported. On the bottom of the screen you will see the menu of choices for your Production Value.

In order to select a Production Value simply use your mouse to click in the circle to the left of the value you wish to choose. After clicking in one of the circles you MUST click the Confirm button before your choice will be submitted. If you wish to change your choice you may do so at any time BEFORE clicking the Confirm button. You may change your choice of Production Value as many times as you wish. However, once you have clicked the Confirm button you will NOT be able to change your Production Value for the current market. After you have clicked Confirm a results screen will appear and inform you of your Profits for the current market. Once you have finished viewing these results click Continue to move on. After you have clicked Continue, you will proceed to the next market where you will be given the new market's Marketing Reports and asked to make a production choice for that market.



After you have made production choices for 30 markets the session will be over. A screen will appear informing you of your Total Profits and Total Earnings. Your Total Earnings are the amount you will be paid in cash. Your Total Earnings are calculated by dividing your Total Profits by 6,000. In other words for every $6,000 in Profits that you made you will earn $1.00 in cash. For instance, if you earn a Total Profit of $96,000 then your Total Earnings will be $16. If you did not choose to receive a hang tag for parking then you will receive a $5.00 show-up fee in addition to your Total Earnings. In that case your Total Payment will be calculated by adding the $5.00 show-up fee to your Total Earnings. So in the above example your Total Payment would be $16.00 + $5.00 or $21.00 in cash. However, if you did choose to take a hang tag for parking your Total Payment will be the same as your Total Earnings. Once the session is over and everyone has viewed their Total Earnings you will be called up, one at a time, to be paid privately and in cash. The session will not be finished until everyone has made decisions for all 30 of their markets. After you have finished please wait patiently for all remaining markets to finish.

Appendix B – Individual Data

Table V: Individual MSDs for CBDT and MAX Predictions

Immediate Feedback				Delayed Feedback			
w/ Current		w/o Current		w/ Current		w/o Current	
CBDT	Max	CBDT	Max	CBDT	Max	CBDT	Max
0.933	1.333	1.533	0.533	1.067	1.733	1.467	1.067
1.200	1.400	1.400	1.067	0.733	1.267	1.200	1.333
1.600	0.867	1.333	1.067	0.600	1.667	1.467	0.467
0.933	1.467	1.333	0.733	1.200	1.333	1.333	0.933
0.667	1.467	1.267	1.267	0.667	1.667	1.400	0.933
1.667	1.733	1.600	0.600	0.933	1.067	1.333	1.467
1.333	1.333	1.667	1.067	0.333	1.667	1.533	0.133
1.533	0.467	1.533	1.333	0.733	1.067	1.333	1.267
1.533	0.200	1.333	0.600	1.467	0.067	1.533	1.600
1.133	1.067	1.333	0.400	1.000	1.600	1.467	1.533
1.333	1.267	1.400	1.333	1.267	1.200	1.200	1.133
1.267	1.533	1.600	1.067	1.333	1.533	1.267	1.400
1.467	0.867	1.333	1.133	1.067	1.533	1.533	1.600
1.267	1.133	1.133	0.667	1.133	1.000	1.267	1.000
1.000	1.200	1.067	1.067	1.200	1.533	1.400	1.533
1.200	1.000	1.200	1.533	0.467	1.533	1.333	1.333
0.600	1.467	1.333	1.000	1.467	1.200	1.467	1.067
0.667	1.200	1.200	0.867	1.000	1.133	1.600	1.467
1.467	0.600	1.467	1.067	1.333	1.067	1.400	1.200
1.333	0.933	1.200	1.333	1.400	1.133	1.267	1.533
1.333	1.533	1.667	0.333	0.867	1.267	1.267	1.267
1.200	1.000	1.533	0.467	1.533	1.333	1.400	0.600
1.467	1.267	1.267	1.067	1.467	0.200	1.533	1.667
0.400	1.600	1.467	1.200	1.267	1.067	1.267	1.333
1.733	1.333	1.400	1.333	0.200	1.733	1.533	0.933
1.600	0.933	0.867	1.667	1.400	1.467	1.267	1.200
0.667	1.400	1.467	1.000	1.067	1.800	1.600	0.733
1.467	1.400	1.600	1.467	1.000	0.867	1.733	0.467
0.600	1.267	1.133	1.333	0.733	1.600	1.533	0.867
1.000	1.600	1.600	0.600	0.933	1.200	1.200	1.200
0.933	1.267			1.200	1.267	1.333	1.333
1.133	1.200			0.200	1.467		
1.600	0.067			0.733	1.733		
1.067	1.067						
1.267	1.400						
0.800	1.467						
1.200	1.133						
1.600	1.133						
1.133	1.267						

Table VI: Blocks of 15 rounds of Individual MSDs for CBDT and MAX (w/ Current)

Immediate Feedback				Delayed Feedback			
CBDT		Max		CBDT		Max	
1–15	16–30	1–15	16–30	1–15	16–30	1–15	16–30
0.800	1.067	1.467	1.200	1.333	0.800	1.733	1.733
1.200	1.200	1.467	1.333	0.400	1.067	1.600	0.933
1.600	1.600	1.067	0.667	0.267	0.933	1.467	1.867
1.067	0.800	1.200	1.733	1.067	1.333	1.600	1.067
1.200	0.133	1.467	1.467	0.933	0.400	1.867	1.467
1.867	1.467	1.733	1.733	0.667	1.200	0.933	1.200
1.467	1.200	1.467	1.200	0.400	0.267	1.600	1.733
1.467	1.600	0.800	0.133	1.067	0.400	0.400	1.733
1.467	1.600	0.400	0	1.333	1.600	0.133	0
1.067	1.200	0.933	1.200	1.333	0.667	1.733	1.467
1.600	1.067	1.600	0.933	0.933	1.600	1.600	0.800
1.467	1.067	1.467	1.600	1.200	1.467	1.467	1.600
1.467	1.467	1.200	0.533	0.800	1.333	1.733	1.333
1.333	1.200	1.333	0.933	1.333	0.933	0.800	1.200
0.933	1.067	1.200	1.200	1.067	1.333	1.733	1.333
1.333	1.067	1.067	0.933	0.533	0.400	1.600	1.467
0.800	0.400	1.600	1.333	1.333	1.600	0.933	1.467
0.800	0.533	1.200	1.200	1.333	0.667	1.067	1.200
1.467	1.467	0.800	0.400	1.600	1.067	1.067	1.067
1.330	1.333	0.800	1.067	1.333	1.467	1.333	0.933
1.200	1.467	1.467	1.600	0.933	0.800	1.467	1.067
1.067	1.333	1.200	0.800	1.467	1.600	1.067	1.600
1.600	1.333	1.200	1.333	1.600	1.333	0.133	0.267
0.667	0.133	1.733	1.467	1.067	1.467	1.333	0.800
1.867	1.600	1.333	1.333	0.267	0.133	1.733	1.733
1.467	1.733	1.067	0.800	0.933	1.867	1.333	1.600
0.800	0.533	1.200	1.600	1.333	0.800	1.733	1.867
1.067	1.867	1.467	1.333	1.067	0.933	1.067	0.667
0.533	0.667	1.333	1.200	0.800	0.667	1.867	1.333
0.933	1.067	1.733	1.467	1.200	0.667	0.933	1.467
1.200	0.667	1.067	1.467	1.200	1.200	0.933	1.600
1.200	1.067	1.333	1.067	0.400	0	1.333	1.600
1.600	1.600	0.133	0	0.933	0.533	1.867	1.600
1.067	1.067	1.333	0.800				
1.200	1.333	1.333	1.467				
1.200	0.400	1.467	1.467				
1.067	1.333	1.067	1.200				
1.333	1.867	1.333	0.933				
0.800	1.467	1.333	1.200				

Table VII: Blocks of 15 rounds of Individual MSDs for CBDT and MAX (w/o Current)

Immediate Feedback				Delayed Feedback			
CBDT		Max		CBDT		Max	
1–15	16–30	1–15	16–30	1–15	16–30	1–15	16–30
1.467	1.600	0.800	0.267	1.200	1.733	1.467	0.667
1.333	1.467	1.333	0.800	1.467	0.933	1.200	1.467
1.333	1.333	1.333	0.800	1.600	1.333	0.400	0.533
1.200	1.467	0.933	0.533	1.333	1.333	0.800	1.067
1.333	1.200	1.200	1.333	1.200	1.600	0.933	0.933
1.333	1.867	0.800	0.400	1.200	1.467	1.467	1.467
1.467	1.867	1.333	0.800	1.467	1.600	0.267	0
1.467	1.600	1.600	1.067	1.333	1.333	1.333	1.200
1.067	1.600	0.800	0.400	1.467	1.600	1.600	1.600
1.333	1.333	0.400	0.400	1.467	1.467	1.467	1.600
1.333	1.467	1.200	1.467	1.333	1.067	1.067	1.2
1.600	1.600	1.333	0.800	1.333	1.2	1.333	1.467
1.067	1.600	1.733	0.533	1.467	1.600	1.733	1.467
1.200	1.067	0.800	0.533	1.333	1.200	0.667	1.333
0.800	1.333	1.467	0.667	1.333	1.467	1.600	1.467
1.333	1.067	1.467	1.600	1.333	1.333	1.200	1.467
1.067	1.600	1.333	0.667	1.200	1.733	1.467	0.667
1.067	1.333	0.800	0.933	1.600	1.600	1.467	1.467
1.333	1.600	1.633	0.533	1.467	1.333	1.067	1.333
1.333	1.067	1.067	1.600	1.067	1.467	1.467	1.600
1.600	1.733	0.533	0.133	1.467	1.067	1.200	1.333
1.467	1.600	0.667	0.267	1.467	1.333	0.533	0.667
1.200	1.333	1.200	0.933	1.600	1.467	1.867	1.467
1.467	1.467	1.333	1.067	1.333	1.200	1.600	1.067
1.333	1.467	1.200	1.467	1.733	1.333	1.067	0.800
1.067	0.667	1.467	1.867	1.333	1.200	1.333	1.067
1.467	1.467	1.200	0.800	1.600	1.600	1.067	0.400
1.600	1.600	1.733	1.200	1.733	1.733	0.800	0.133
1.200	1.067	1.467	1.200	1.600	1.467	0.933	0.800
1.600	1.600	0.533	0.667	1.333	1.067	0.933	1.467
				1.200	1.467	1.200	1.067

Appendix C – More Screenshots

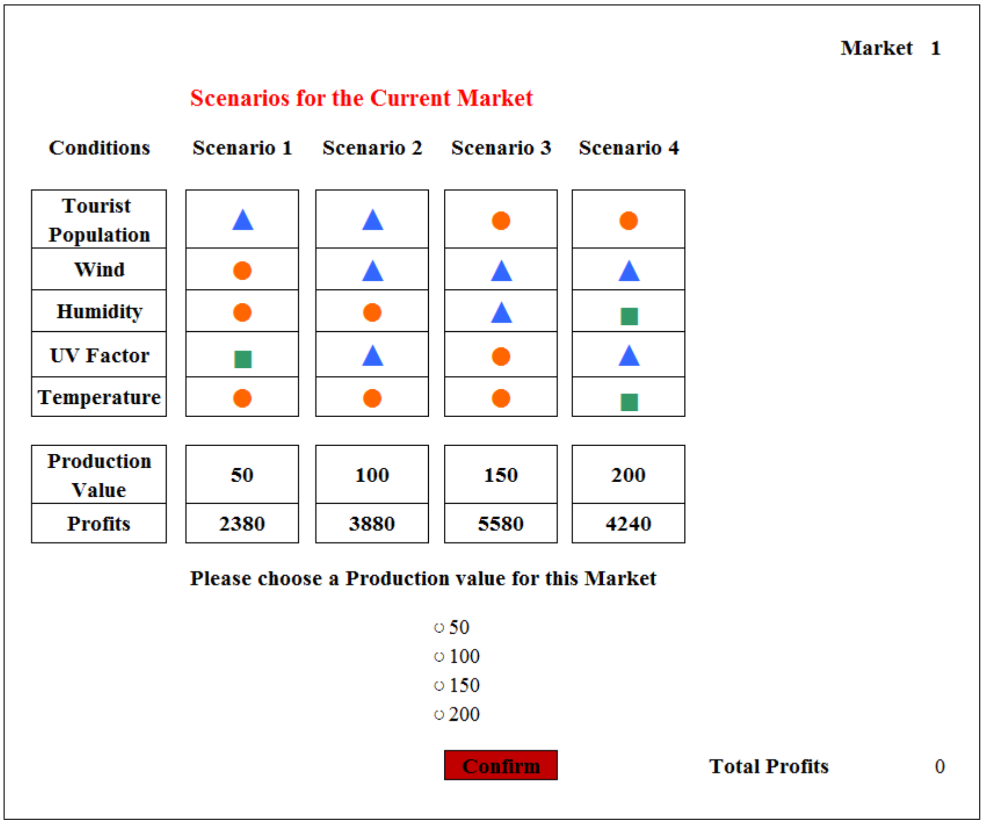


Figure 1: Figure 4: Screenshot of Immediate without Current

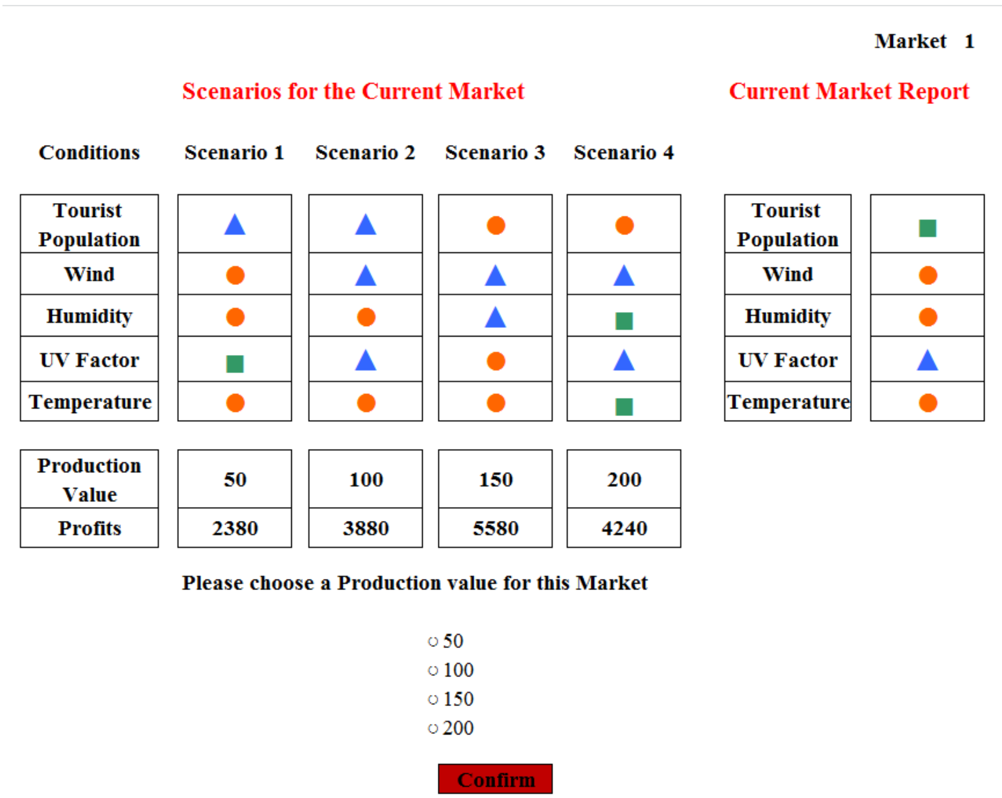


Figure 5: Screenshot of Delayed with Current

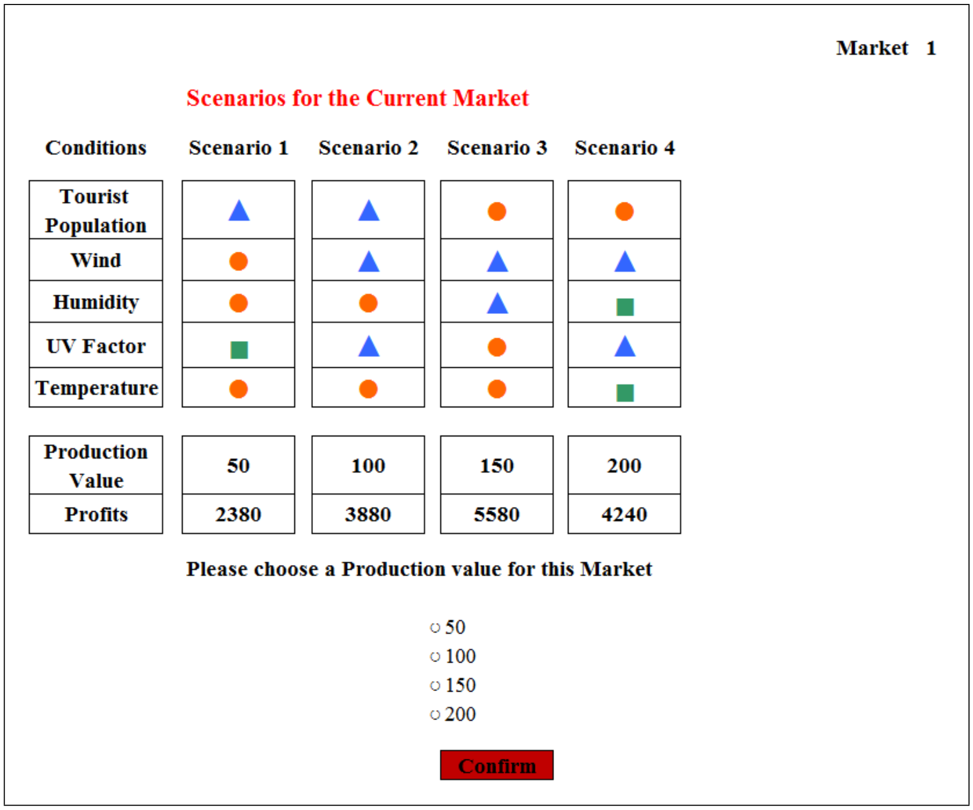


Figure 6: Screenshot of delayed without Current